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Analyzing the Power Market and Projecting the Future with High Energy and Carbon Prices: A Machine-Learning Approach

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Abstract— Increasing shares of renewables in the energy matrix is linked to increased power price fluctuations, which, in turn, increases the financial risks for electricity market participants. In this context, understanding the key factors driving the power prices and thereby improving price forecasts is increasingly important. Here we analyze the main drivers of power prices with the help of machine learning. We show how the selection of the predictors set and length of historical data affect the forecast accuracy of the power prices. Using the developed model, we project how high energy and carbon prices may affect future electricity prices.

Keywords—Electricity Price Forecasting, Machine Learning, Feature Selection, Day-Ahead Market

I. Introduction

A. Motivation

In the transition to a carbon-neutral future, rapid decarbonization of the power sector— the largest emitter of greenhouse gases globally [1], is of great importance. State policies supporting the deployment of renewable energy sources (RES), accompanied by sharp reductions in production costs, have helped to grow the share of RES in the power generation mix in many countries worldwide. In Germany, for example, the RES share in the gross electricity output has surpassed 40% in 2021, doubling over the past decade [2]. However, the growth in the share of RES has been linked to increased power price fluctuations [3]–[7], posing higher financial risks for electricity market participants. Specifically, the price fluctuations affect the cost and attractiveness of investing in non-RES power generation, raising further concerns regarding the reliability [7] and affordability of electricity in the long run. The relationship between the power prices and RES generation is complex and changes over time in a non-trivial manner. In this context, understanding what drives the power prices and how the prices may change in the future is critical for navigating the power sector decarbonization.

In recent years, Electricity Price Forecasting (EPF) has become a popular area of research. Traditionally, EPF has relied on econometrics and statistical methods, but data availability and advances in computational capabilities have allowed machine-learning (ML) and deep learning (DL) methods to dominate the field since the mid-2010s [8]. Despite the numerous studies on EPF, there is still no consensus on what determines the electricity price dynamics. The machine learning approaches to EPF compete in the dimensionality of their databases but offer limited insight into how important the inclusion of additional variables in the analysis is. Targeting energy traders, existing models primarily focus on (ultra) short-term prices comparing the accuracy of hourly, weekly, or monthly predictions using tens (or often hundreds) of variables. The reported results, however, leave open questions regarding the accuracy of longer-term predictions and the predictability of prices with a smaller set of variables. The answers to those questions are essential to inform and support the decisions of energy users and regulators amid the ongoing energy transition.

The objectives of this study are three-fold:

(i) to use an ML approach to identify the key drivers of the electricity prices in the German day-ahead (DA) power market, selecting out of 80 relevant variables, including features highlighting the role of RES;

(ii) to analyze how the length of time series and the distance between the last data point and the predicted outcome may affect the accuracy of the predictions, emphasizing the role of the power sector transformation;

(iii) to demonstrate how the EPF model may be used for normative analysis to make projections on how the future fossil fuel and carbon price changes may affect the affordability of electricity.

For our analysis, we select a set of ML algorithms and ML-based procedures that (1) help discern the macro-behaviors and sub-patterns within the system and (2) allow for interpretability of the results to provide useful economic insights. The proposed methodology includes the steps in training set selection, key feature identification, model optimization, and prediction error quantification. To this end, we employ a variety of tree-based models, including random forest, gradient boosted trees and Bayesian additive regression trees.

Starting with a set of 80 variables characterizing the German DA electricity market, we perform feature selection to rank the predictors and pinpoint the key drivers of the power prices. We examine how the choice of the predictor set affects the model performance. In addition, we test for historical and sample biases. Finally, we build an ensemble model with the selected feature set to develop power price projections for several future scenarios with varying assumptions on the input energy and carbon price developments.

B. Literature Review

The research on EPF and ML methods is vast and fast evolving. The literature can be categorized along several dimensions, including the modeling approach, the time horizon of the predictions, the time granularity of the models, and the energy markets analyzed. [10] and [11] provide excellent reviews of relevant studies prior to 2014, while [12] and [8] summarize and compare the recent developments focusing on ML-based techniques. Despite the advances offered, we identify some gaps, which our study tries to address.

In contrast to traditional data-poor economic simulations, few data-driven works provide long-term price forecasting with a horizon of 1 year or longer. Ziel et al. provide a comprehensive list of published research on mid- and long-term EPF up to 2017 [13]. The studies with a longer prediction horizon commonly generate estimations on an annual basis. In contrast, novel ML-based approaches allow and are used to perform the predictions with hourly and daily granularity. The added price details are especially useful when analyzing the impact of RES generation, which varies dramatically throughout the year with the weather patterns.

Mid- and long-term price forecasting studies with lower levels of granularity include the works of [14]–[19], who investigate the daily average prices, [20]–[23] with the focus on the monthly average price, and [9], [24], [25] who study the yearly-average prices. Finally, research on the electricity price drivers, the effect of RES adoption, and changes in energy and carbon prices traditionally relies on structural models [3], [26]–[29], missing insights and granularity offered by ML-based methods.

C. Contribution

In the context of the above discussion, the present work makes several contributions to the previous EPF studies:

1) Analyzing the power price dynamics, we rank the explanatory variables to identify the top predictors, including but not limited to the market fundamentals. Hence, we help link the results of structural and machine learning-based models. Furthermore, by introducing synthetic features, we capture and analyze interaction effects, such as the interplay between fuel and carbon prices.

   Overcoming the weaknesses of previous studies, we pay special attention to multicollinearity in our feature selection analysis [31]–[33]. We test the recursive feature elimination (RFE) technique [34]–[36] and the VSURF algorithm developed by Genuer et al. [32]. The latter, to our best knowledge, has not been previously applied in EPF.

   Selecting the power price determinants, we explore the effect of a smaller set of predictors on the prediction accuracy. The results of this analysis are especially relevant for those who may not have the resources for an extensive database and have to rely on a limited set of input features. Following the recent attempts to make ML more explainable, we report metrics such as SHAP, in addition to the feature importance scores.

2) Focusing on possible biases in the historical data, we present a procedure to evaluate the effect of training window size on model performance. We show how the model choice and the resulting errors may vary depending on the training data sample.

3) Finally, developing an EPF model, we demonstrate how ML-based methods can benefit normative analyses. We create different scenarios to study how different fuel or carbon policies may affect power prices. Existing works with a similar focus rely on structural or econometrics-based methods, limited in the number of input variables included and/or ability to handle trend changes and structural breaks. In contrast, ML models overcome those challenges and present a more robust and insightful tool for policy analysis.

D. Paper Structure

The remainder of the paper is structured as follows. Section 2 introduces the dataset, including the original data and the engineered features, and exploratory data analysis. Section 3 introduces the methodology discussing the models and tests used. Section 4 presents the results, including the findings of the feature selection analysis, the effects of the calibration window size on predictive performance, and an overview of the relevant accuracy metrics. Section 4C reports the scenario analysis outcome. We provide the conclusions and summary of our work in Section 5.

II. Data

In line with the primary goal of our research, we collect 80 variables capturing the recent developments in the German DA power market from January 2015 to October 2021. Our power market choice is motivated by the larger volume of RE traded on the DA market [37] and the role of DA prices as reference point in energy trading [38]. We include variables such as the electricity prices of Germany and neighboring countries, daily values and day-ahead forecasts of total load and the infeed from wind and solar generation.

As prices are determined by the supply composition, we add electricity generation per plant type and imports and exports from neighboring countries to the database. Since ~60% of the gross power output is provided by non-RES generation, namely by fossil fuels, we include coal API2 and natural gas TTF prices. To account for the role of carbon regulations, we use the EUA carbon prices. In addition to the listed, we introduce two synthetic variables, namely coal and natural gas "clean prices" to capture the interactive effects of carbon prices with fossil fuel prices. The clean price is calculated based on the underlying fuel price plus an additional mark-up corresponding to the associated carbon costs resulting from the use of the fuel in power generation [39].

Apart from the cost drivers, we include other determinants of the power prices such as weather and other non-economic variables. These include temperature, humidity, dew point, wind speed, and global irradiance factor, as well as variables representing holidays, weekends, days of the week, and seasons. All explanatory features, except for the day-ahead forecasts, are lagged by one day to reflect the information that is available to the market participants in predicting the day-ahead power prices.

We analyze the compiled dataset by looking at the correlations between the variables and the DA power price (Fig. 1a). The constructed correlation matrix reveals a high correlation between some explanatory features, as marked by

TABLE I. THE IDENTIFIED TOP DRIVERS OF POWER PRICES IN GERMANY USING DIFFERENT FEATURE SELECTION TECHNIQUES

	RFE with RF	***VSURF Interpret with RF***	***VSURF Predict with RF***	***RFE with BART***	***RFE with XGBOOST***
1	Coal clean price (day-before)	Coal clean price (day-before)	Coal clean price (day-before)	NG clean price (day-before)	Coal clean price (day-before)
2	EUA carbon price (day-before)	Forecast residual load (day of)	Forecast residual load (day of)	Forecast residual load (day of)	Forecast residual load (day of)
3	Forecast residual load (day of)	NG clean price (day-before)	NG clean price (day-before)	EUA carbon price (day-before)	EUA carbon price (day-before)
4	Coal price (day-before)	Coal price (day-before)		Coal price (day-before)	NG clean price (day-before)
5	NG clean price (day-before)	EUA carbon price (day-before)		Coal clean price (day-before)	NG price (day-before)

the dark blue and yellow colors. The observed correlations are found to change over time. Figs. 1b-d illustrate the changes in the correlations between the day-ahead price and four explanatory variables over three time periods, highlighting the importance of moving beyond a simple correlation (or regression) analysis to more sophisticated approaches that can adequately capture, explain, and project the power market behavior.

III. METHODOLOGY

Following the previous studies, we select three distinct tree-based ML models for (1) their ability to capture non-linear behavior, without the need for input data transformation, and (2) the ease of interpretability. The used techniques include random forest (RF), extreme gradient boosted trees (XGBoost) and Bayesian additive regression trees (BART). We compare several feature selection techniques to rank the input features according to their role in model performance. We apply "VSURF interpret", "VSURF predict" [32], and recursive feature elimination (RFE) with cross-validation as proposed by [34]–[36] to RF. The latter is also used for XGBoost. For BART, we select RFE with replication. These procedures allow to account for possible biases stemming from the strong correlation of the input features [31]–[33].

Having ranked the input features, we reapply our models to the reduced set of variables, assessing the accuracy of predictions for each test year in 2016-2021. In total, we test 11 models that vary with regard to the input feature set and the utilized algorithm. For each test year, information from the previous years is used in EPF for the entire next year. To control for possible historical biases stemming from the significant changes in the energy sector, we also examine the effect of the model calibration window. Further details on the methodology are provided in the supplementary material.

Inspired by [12], we create an ensemble model consisting of the output from several of the 11 developed models and compare the predictive performance against the base models. Finally, we use the ensemble model for the normative analysis projecting how the power prices react to the changes in input energy and carbon prices.

IV. RESULTS

A. *Feature Selection and the Drivers of Power Prices*

We start the reporting of our results with the feature selection analysis. The findings strongly support the conclusion that the top 5 drivers of the electricity prices in Germany during the analyzed period are energy input prices corrected for carbon and the demand unsatisfied by renewable generation (Table I). The different selection techniques show how the ranking of these variables concerning their importance may be different, but that the members of the list stay the same. Beyond the top 5 variables, the selection techniques agree on > 60% of the top 15 features and > 68% of the selected top 50 features. The complete list of the variable rankings is found in the supplementary material.

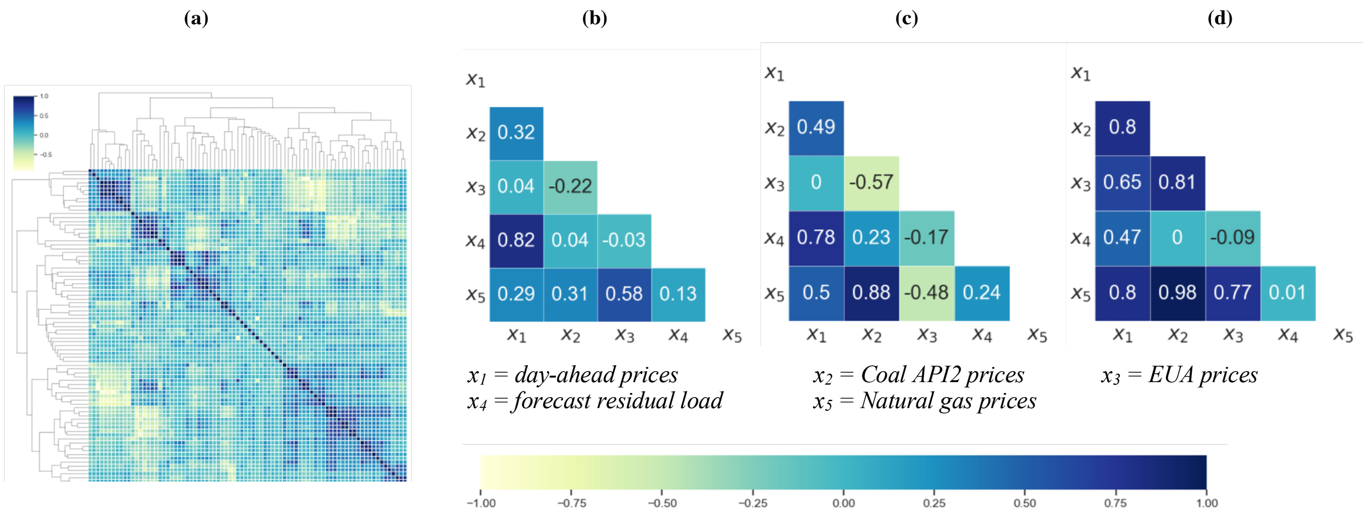

Fig. 1. Pearson's correlation matrix for the employed dataset. The input features exhibit a high level of multi-collinearity (a). The inter-correlation of the day-ahead power prices with four selected features evolves over the period of 2015-2017 (b), 2018-2020 (c) and 2020 (d)

TABLE II. TEST STATISTICS OF THE TOP SELECTED MODEL FOR EACH OF THE PREDICTION YEARS 2016 TO 2021

Year	Actual Data		Test Data					
	Mean	*Standard Deviation*	*Top Model*	*RMSE*	*MAE*	*rMAE*	*MAPE*	*Optimum Calibration Window*
2016	28.98	9.65	Ensemble	**5.12**	3.66	0.70	0.31	1 year (2015)
2017	34.20	14.00	Ensemble	**6.46**	3.79	0.47	0.13	1 year (2016)
2018	44.47	14.31	BART_top15	**8.96**	6.81	0.84	0.20	1 year (2017)
2019	37.67	11.85	Ensemble	**4.91**	3.58	0.48	0.23	2 years (2017 + 2018)
2020	30.47	13.94	Ensemble	**6.23**	4.78	0.58	0.28	4 years (2016 to 2019)
2021	74.81	38.44	VSURF Predict with RF	**39.43**	24.95	1.75	0.29	5 years (2016 to 2020)

**RMSE = Root mean square error, MAE = Mean absolute error, rMAE = Relative mean absolute error, MAPE = Mean absolute percentage error*

The correlation analysis has already suggested that out of 79 variables, only a smaller subset of features play a critical role in explaining the variance in the power prices. The results from "VSURF predict" and "VSURF interpret" appear to support this preliminary intuition. Although none of the variables can individually predict the power prices, "VSURF predict" suggests that the set of clean coal and natural gas prices together with forecasted residual load are sufficient for a good prediction of the power prices, while "VSURF interpret" indicates a selection of 12 features to fully capture and interpret the price dynamics.

Apart from permutation-based variable importance scores, which measure the impact of the features on the prediction performance (e.g., the model RMSE score), we estimate Shapley values to determine the contributions of the individual variables to the model predictions. Averaging the marginal contribution of the features over the entire data set, we calculate the "global" SHAP feature importances [40] and show how the average feature contributions may align with the feature rankings, e.g., in the test year 2019 for the XGBoost model (Fig. 4). However, we prefer not to rely on the SHAP estimates because, as discussed by [41] and [42], these measures can be highly inaccurate for correlated feature sets and thus may not be well-suited for evaluating feature importances.

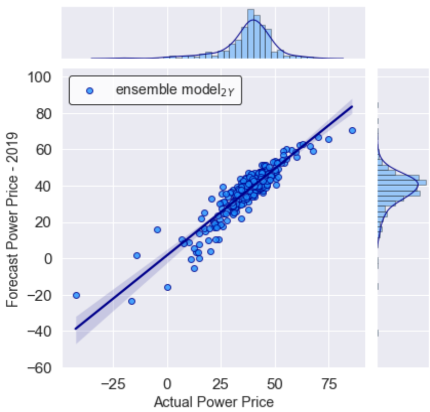

Fig. 2. Predicted vs. actual power prices in 2019

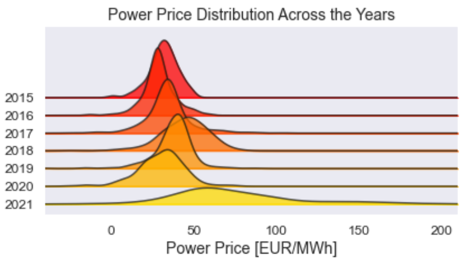

Fig. 3. Daily average power price distributions in years 2015-2021

B. *Predictive performance*

Next, we examine how the length of the historical period, model type, and the choice of explanatory features may affect the accuracy of the price predictions for each test year (Table II). While Table II ranks the models with regard to the root mean square error (RMSE), several additional error statistics are also reported. With the goal to construct an ensemble model with superior results, we test different combinations of the 11 base models. Except for 2018 and 2021, we find the ensemble model consisting of "VSURF predict", BART, and XGBoost to outperform the base models in all test years. In 2018 and 2021, Europe witnessed unprecedentedly high fossil fuel and power prices, well outside the range of the price distributions seen in the previous years (Fig. 3). Hence, we attribute the poorer prediction performance (as evident from the error statistics) in these years to the known weakness of ML algorithms: the inability to extrapolate.

For the years 2016-2018, we find a shorter history of one year to result in better prediction performance, while for the later test years including a more extended history appears to be the most advantageous. This is especially the case for 2021, characterized by a broad density distribution, for which a data history from 2016 onwards is necessary.

Regarding the choice of the explanatory features, the results suggest that selecting the top 15 variables for BART and XGBoost and the three input variables for "VSURF predict" would produce the optimal results. This requires a total of 19 variables from the original dataset, as the models' feature sets are different. Including more variables appears to worsen the prediction performance due to the issue of overfitting.

C. *Scenario Analysis*

Shifting our focus from positive to normative analysis, we use the developed models to investigate how a step shift in fossil fuel and/or carbon prices may affect the power prices throughout the year. Applying the ensemble models, we develop price *projections* (in contrast to *predictions*) by analyzing four scenarios in which we vary the prices of natural gas, coal, and carbon certificates, either individually or in combination, assigning to each the corresponding median value observed within the last three months in our database. Such an exercise allows us to see the DA power price reaction to an increase in the input prices over a 365-day horizon, with

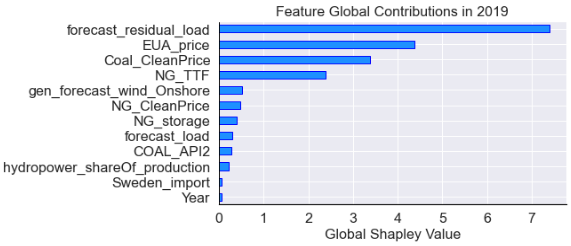

Fig. 4. Average feature contributions in 2019 for XGBoost model

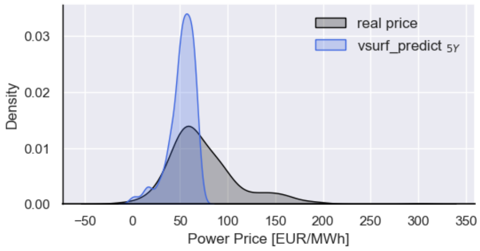

Fig. 5. Predicted vs. actual power prices in 2021

2019 as the benchmark year. keeping the original values for all the included variables, except those listed in the scenario details (Table III). We

Based on the previous model and feature selection analyses, we use an ensemble of "VSURF predict" with RF and XGBoost and RF with their respective set of top 15 features for the projections. In contrast to Section 4B, we do not include BART in the ensemble model for the scenario analyses due to the instability of its output, highly dependent on the initial seed.

We present the results for scenarios 1 and 3 (Fig. 6 and 7), leaving the complete set of results in the Appendix. Considering the increasing natural gas price in scenario 1, we estimate a positive shift in the power prices across all seasons, with the shape of the price distribution becoming visibly multi-modal. Fixing the value of one main feature at a time allows us to gain insights into how other variables' behavior shapes the power price formation. In scenario 1, the power price distribution gains closer resemblance to the coal price distribution. The change in the price behavior appears more prominent in winter, showcasing the merit-order effect (Figs. 6a and 6b). Contrary to expectation, we do not observe a vast price difference across the seasons, possibly due to the reliance on the gas-fired peaker plants used to complement the intermittent RES.

Repeating this exercise with the carbon prices instead of natural gas helps us highlight the effects on fossil-based generation, which is used more intensively during the winter. In scenario 3, we reveal the interaction between carbon and natural gas prices as both variables are simultaneously increased. The price effect, in this case, appears to be superadditive: the concurrent increase in both carbon and natural gas prices has a greater impact on increasing the power prices compared to the sum of the increases when only one price is raised (scenarios 1 and 2). Finally, in scenario 4, where the prices of coal, natural gas and carbon are increased simultaneously, we find that the power price distribution resembles the load profile, in line with intuition from structural power market models. Hence, we verify our findings concerning the top 5 variables, as we eliminate the factors one by one, moving from scenarios 1 to 4.

TABLE III. Scenario Design

Case	NG price (EUR/MWh)	EUA price (EUR/EUA)	Coal price (EUR/T)	Other variables
1	52	2019 levels	2019 levels	2019 levels
2	2019 levels	59	2019 levels	2019 levels
3	52	59	2019 levels	2019 levels
4	52	59	141	2019 levels

V. Conclusions

In the context of the ongoing energy transition and the recent geopolitical developments, understanding the power price dynamics and the key price determinants is relevant not only for improving price forecasts but, more importantly, for addressing questions related to energy security and affordability. The presented work offers new insights into the power market behavior by analyzing the daily average prices in the day-ahead market in Germany.

Using machine learning, we evaluate the ability to explain the day-ahead power prices with an extensive set of 79 variables. We complement the analysis with various feature selection procedures to report the key drivers behind the power prices. Overcoming the weaknesses of previous studies, we pay special attention to possible biases in feature selection due to the high correlation of the input features.

Linking to structural and econometrics models, we show that forecasted residual load and clean fossil fuel prices are the most important variables in driving the power price dynamics. Putting the above finding into practice, we project the power prices for individual years in 2016-2021.

We examine and report the effects of the input feature set, model selection (RF, XGBoost, BART or an ensemble), and the length of historical data on the forecast accuracy. We find the ensemble model to outperform the other models in all test years except for 2018 and 2021. A calibration window size of one year appears to be sufficient for the earlier test years, but for the later years, particularly 2021, the entire historical information is useful for the most accurate price predictions. The high prediction errors in 2021 highlight the limitations of

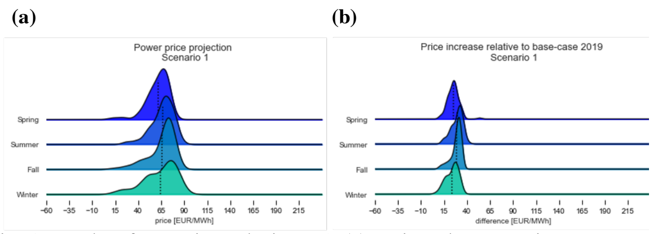

Fig. 6. Results of scenario analysis no. 1. (a) Projected power prices across the seasons, (b) price increase relative to 2019

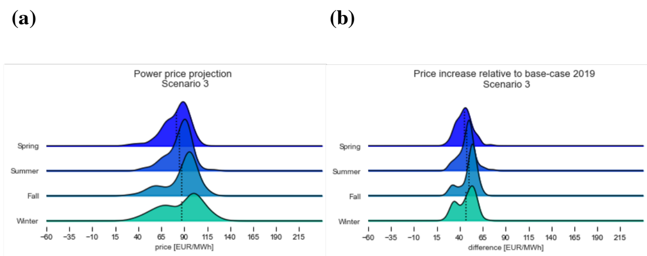

Fig. 7. Results of scenario analysis no. 3. (a) Projected power prices across the seasons, (b) price increase relative to 2019

ML methods in extrapolating beyond the observed range of values in the training set.

Complementing our EPF with normative analysis, we report the insights from four different scenarios characterizing the effect of fossil fuel and carbon prices on the distribution of the power prices across the year. Contrary to expected, we do not detect a significant difference in the level of the price increase across the different seasons of the year in response to increasing fuel prices. We attribute this finding to the increasing reliance on peaking power plants supporting the increasing share of intermittent RES. Moreover, our results indicate that the effects of carbon and fossil-fuel prices may be superadditive. The simultaneous increase of carbon and fossil-fuel prices raises the power prices to a greater degree than when the input prices are increased individually.

Future extensions of this work could include combining the ML methods with parametric models to overcome the issues related to extrapolation.

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